Optech

measurement at the speed of light

Development of High-Level Data Fusion Algorithms for Bathymetric LIDAR and Spectral Data

Optech International

Dr. Joong Yong Park

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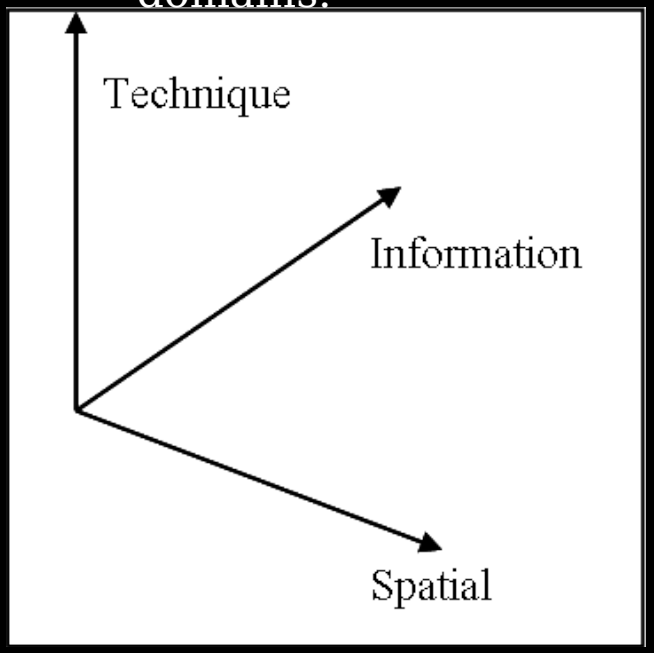
SIT Data Fusion Model

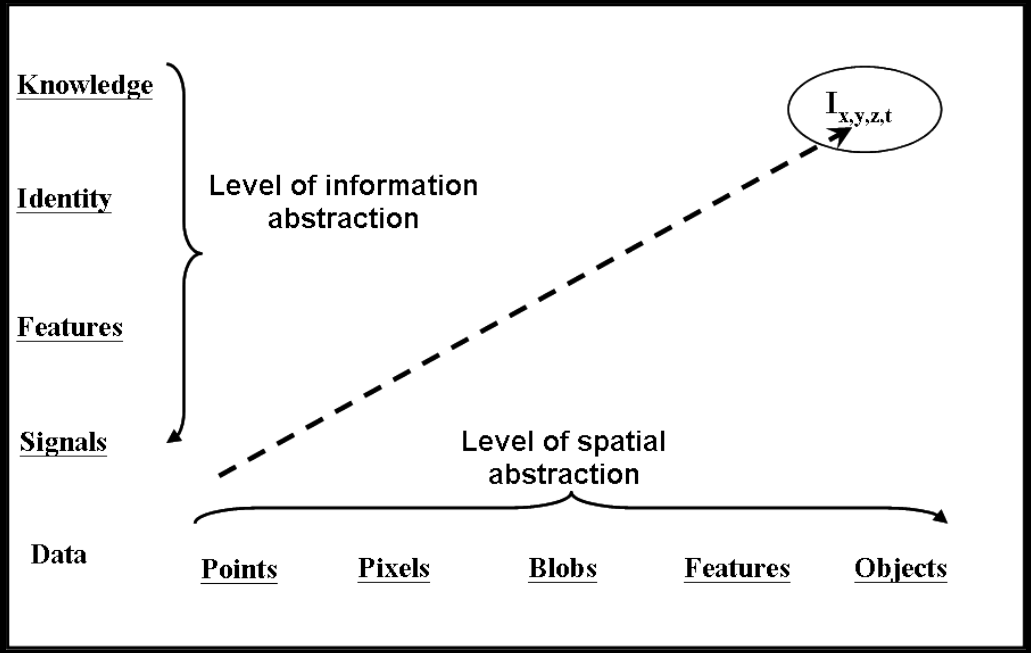
The main goal of this NOPP project is to develop sophisticated strategies for combining airborne remotely- sensed data for the purpose of mapping and monitoring the coastal zone.

A new data fusion paradigm model, SIT :

- Easy to compare different approaches of combining active and passive data
- Easy to describe the progression of a series of connected data processing modules leading to increased levels of abstraction in three domains.



3D SIT concept



Spatial and Information Axes of SIT Model

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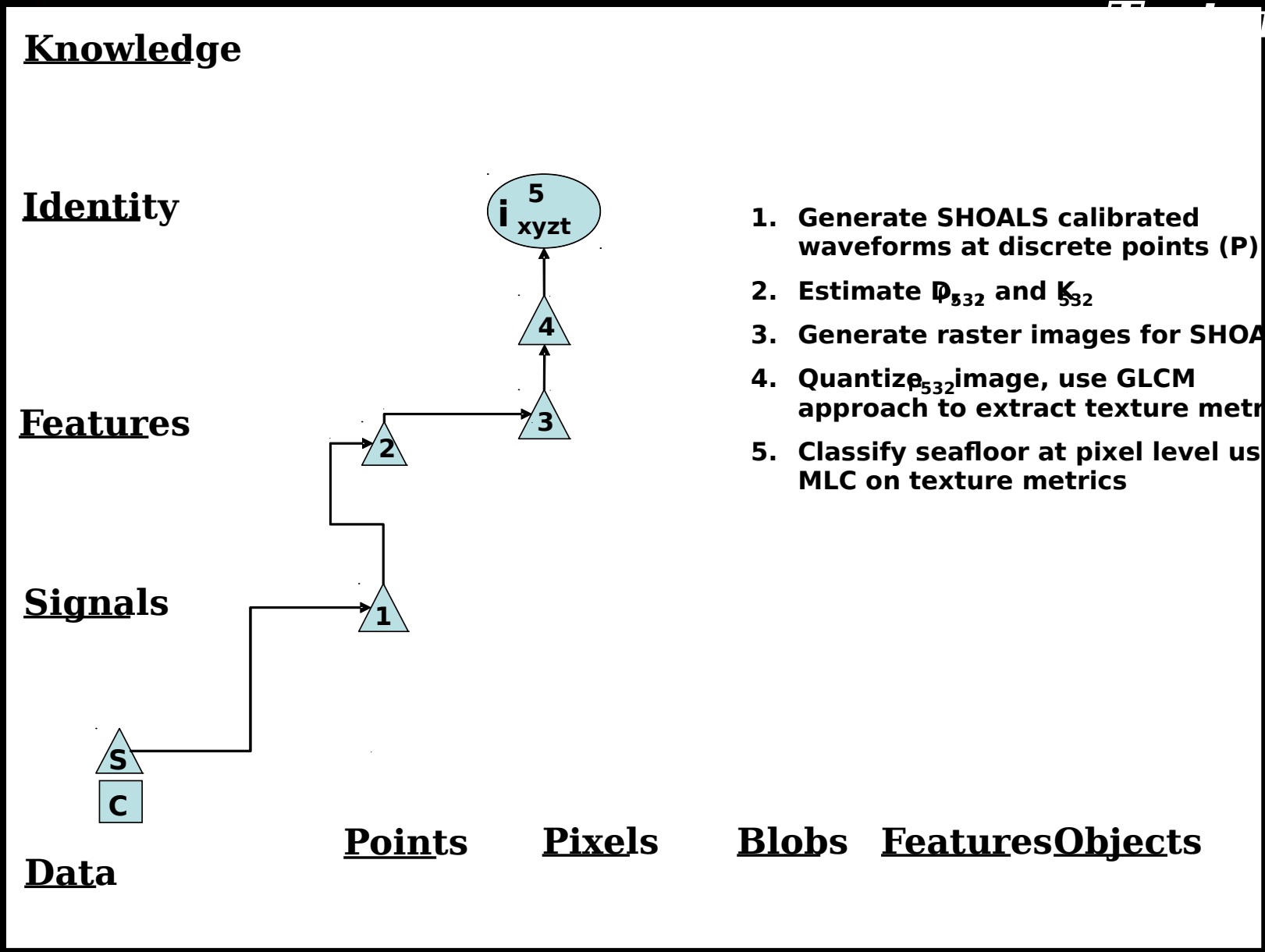
Case 1: *Classification with SHOALS GLCM Texture*



1. Generate SHOALS calibrated waveforms at discrete points (P)
2. Estimate D_{532} and K_{532}
3. Generate raster images for SHOA
4. Quantize $_{532}$ image, use GLCM approach to extract texture metr
5. Classify seafloor at pixel level us MLC on texture metrics

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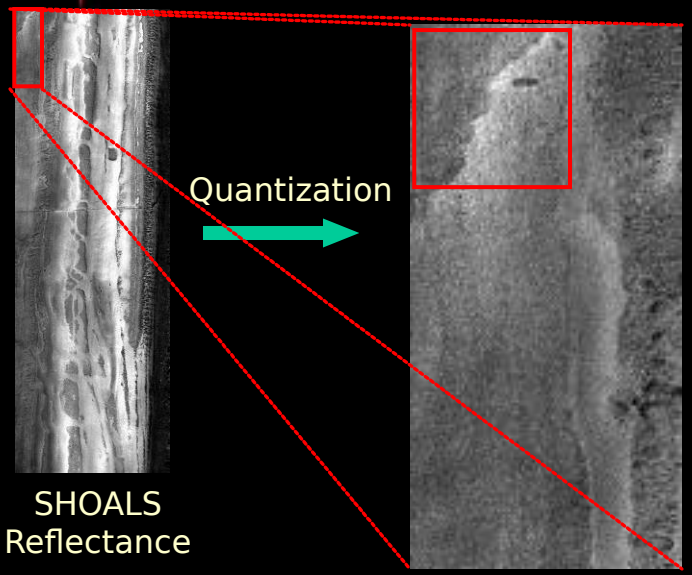
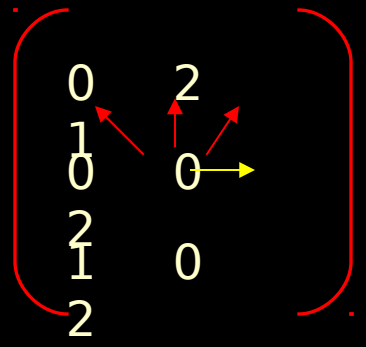
Texture Based Classification



Fix Kernel Size (3X3)

$$\begin{pmatrix} 0 & 2 & 1 \\ 0 & 0 & 2 \\ 1 & 0 & 2 \end{pmatrix}$$



Initialize Co-occurrence direction

0 1 2 ... 63

$$\begin{pmatrix} 1 & 0 & 3 \ldots \\ 1 & 0 & 0 \ldots \\ 0 & 1 & 0 \ldots \end{pmatrix}$$

Ex: Co-occurrence Matrices in horizontal directions

Feature Extraction

0 1 2 ... 63

- Mean
- Variance
- Contrast
- Entropy
- Second moment
- Homogeneity
- Dissimilarity
- Correlation

Feature Space

Average matrices in all the 4 directions

Low Pass Filter

CLASSIFIER

SHOALS TBC Methodology

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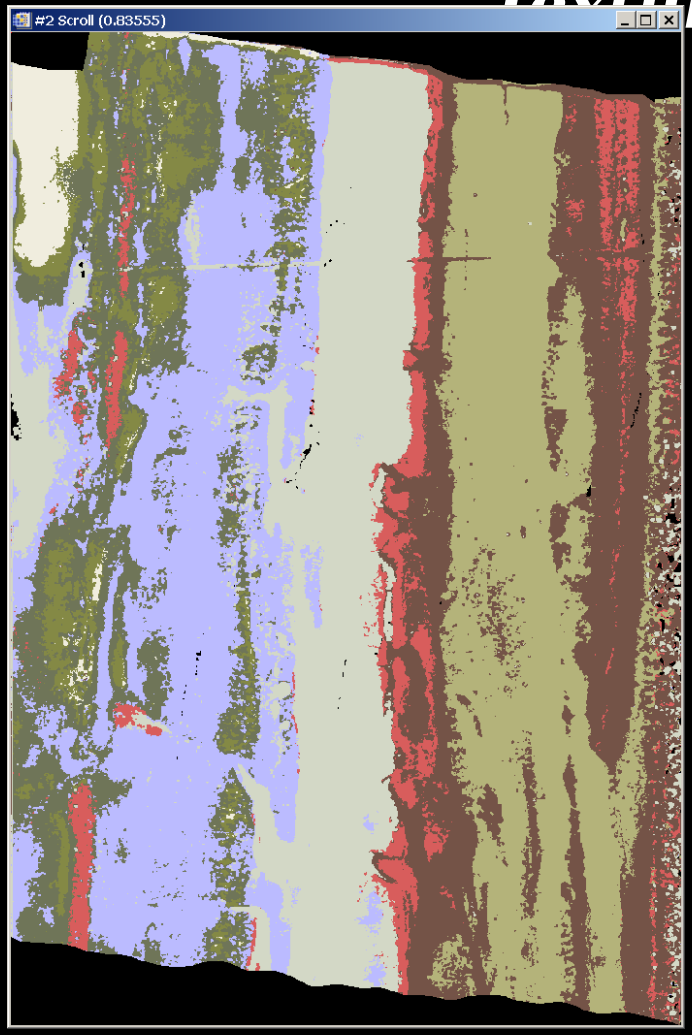
Case 1: Classification with SHOALS GLCM Texture

SHOALS seafloor reflectance image



MLC from SHOALS GLCM Texture

Shallow sand
Hardbottom 1
Mid sand
Hardbottom 2
Channel sand
Hardbotto m 3
Deep Reef sand

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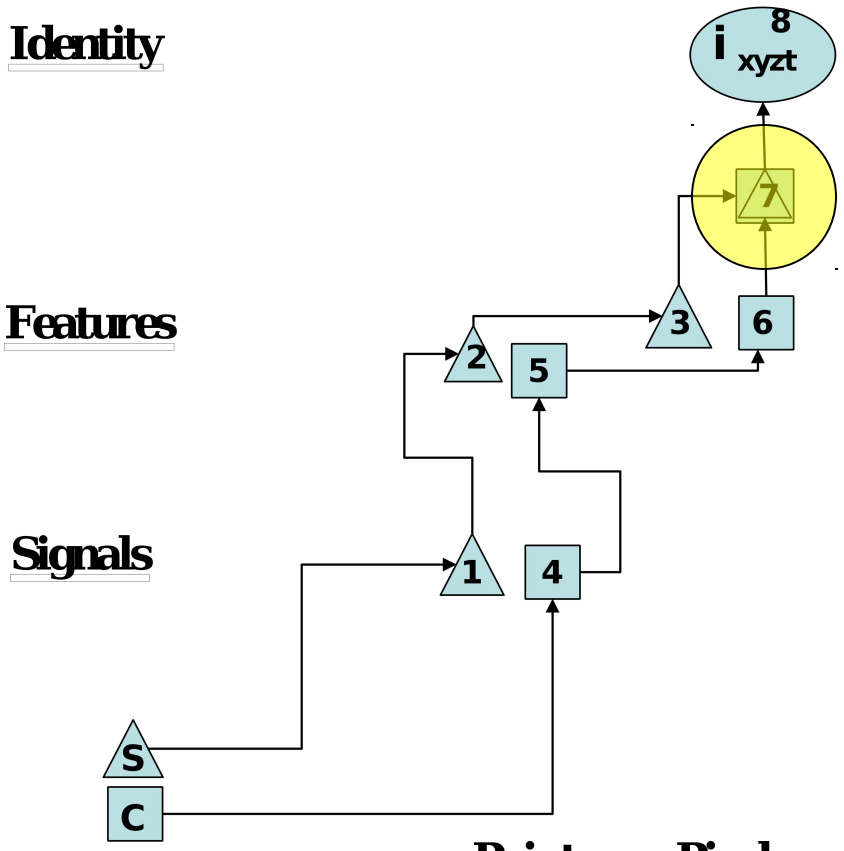
Case 2: Classification with CASI Seafloor Reflectance



1. Generate SHOALS calibrated waveforms at discrete points (P)
2. Estimate D, ρ_{532}, and K_{532}
3. Generate raster images for SHOALS
4. Generate Casi calibrated waveforms at discrete points (L_λ)
5. Pre-process Casi data to remove perturbing effects of atmosphere and sea surface (ρ_λ)
6. Generate ρ^s_λ image at geometric resolution of SHOALS images
7. Invert the RTE for Casi data using D, ρ_{532}, and K_{532} as constraints
8. Classify seafloor at pixel resolution using MLC or SAM

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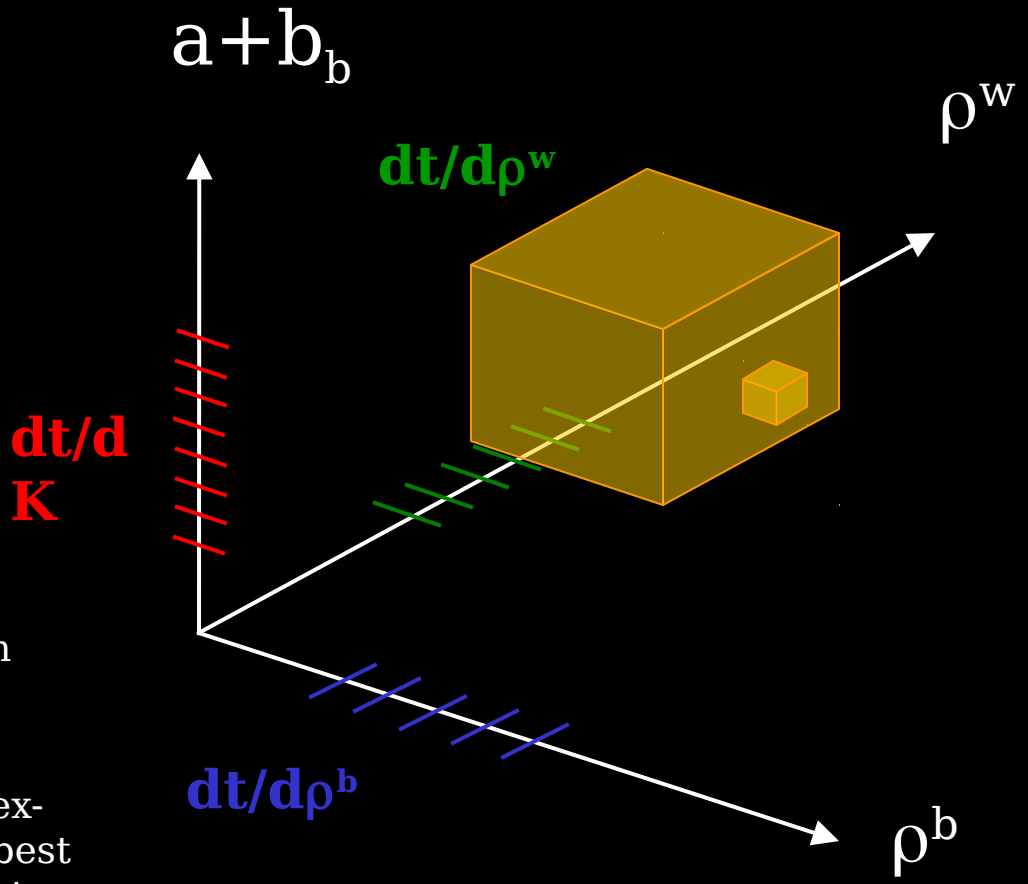
Constrained Inversion Strategy



Stochastically speaking: we use depth as a fixed constraint, and reflectance and attenuation from SHOALS as weak constraints.

The constrained solution is performed as a numerical simplex-type approach. This cannot be “best linear uniformly unbiased estimate (BLUE)”

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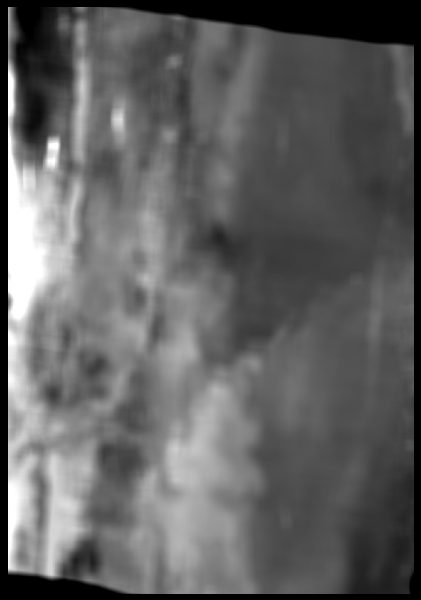
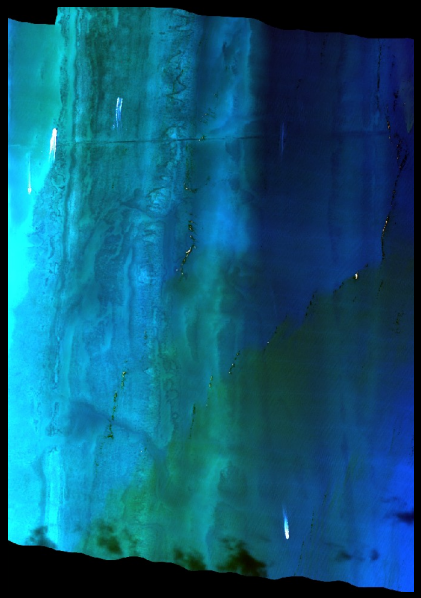
Input Images for Constrain Inversion

SHOALS Depth

SHOALS Seafloor Reflectance



SHOALS ($a+b_b$)



CASI Surface Reflectance

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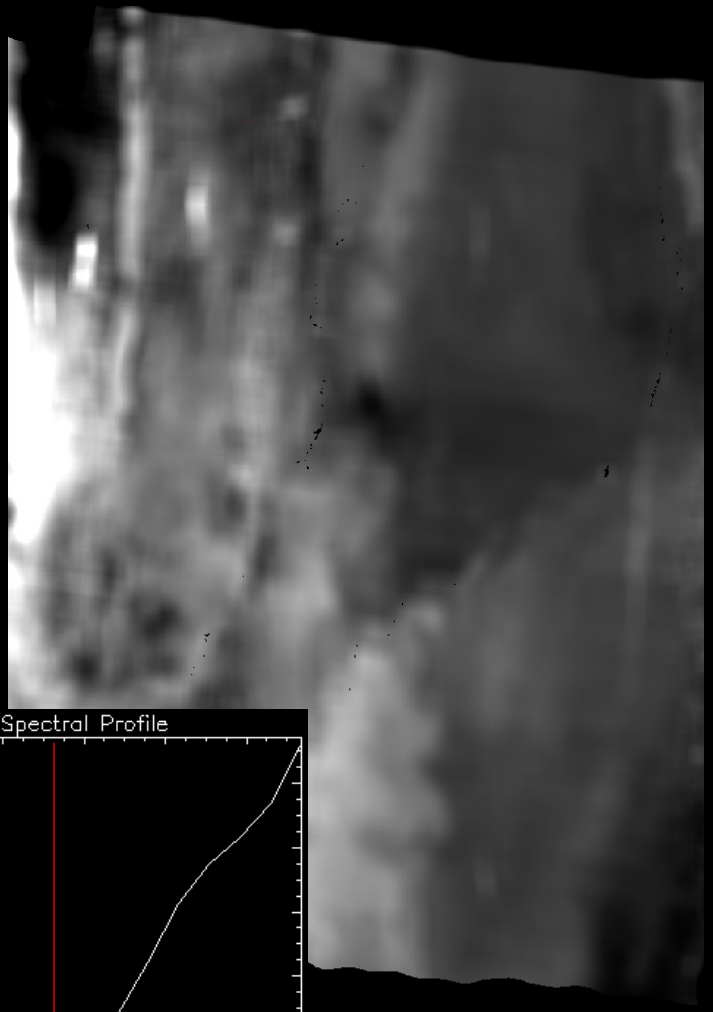
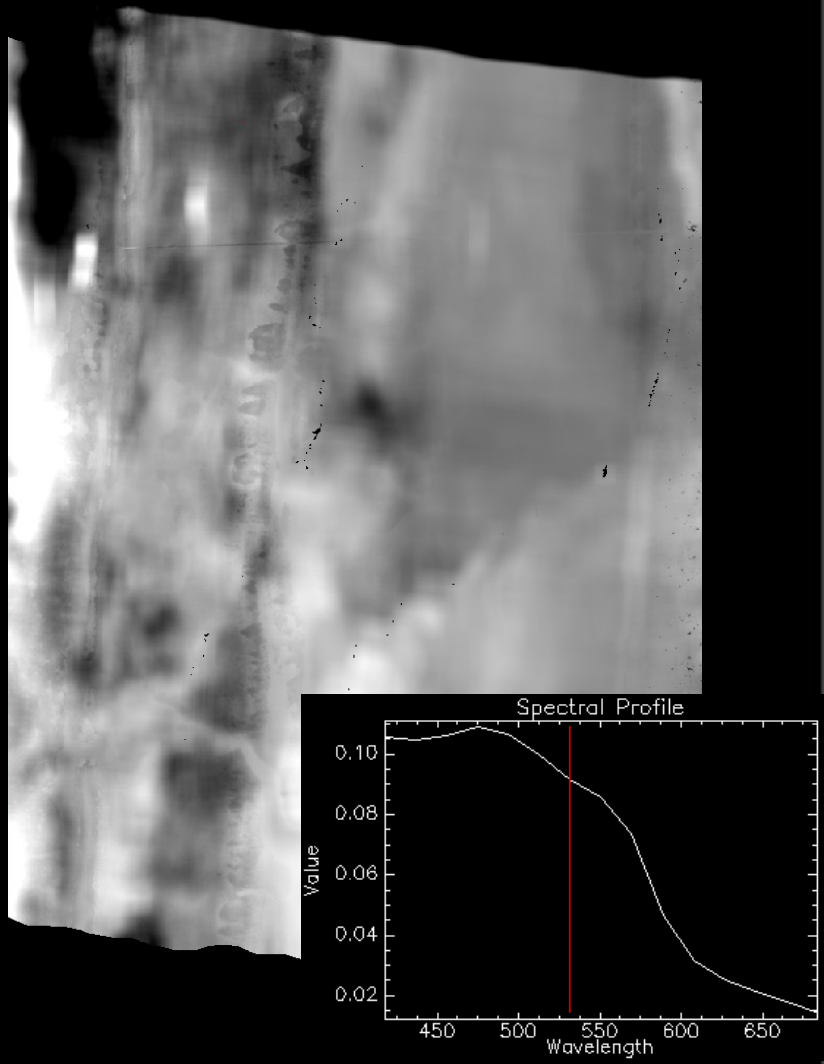
Product Images from Constrain Inversion



CASI diffuse attenuation (534 nm)



CASI volume reflectance (534 nm)

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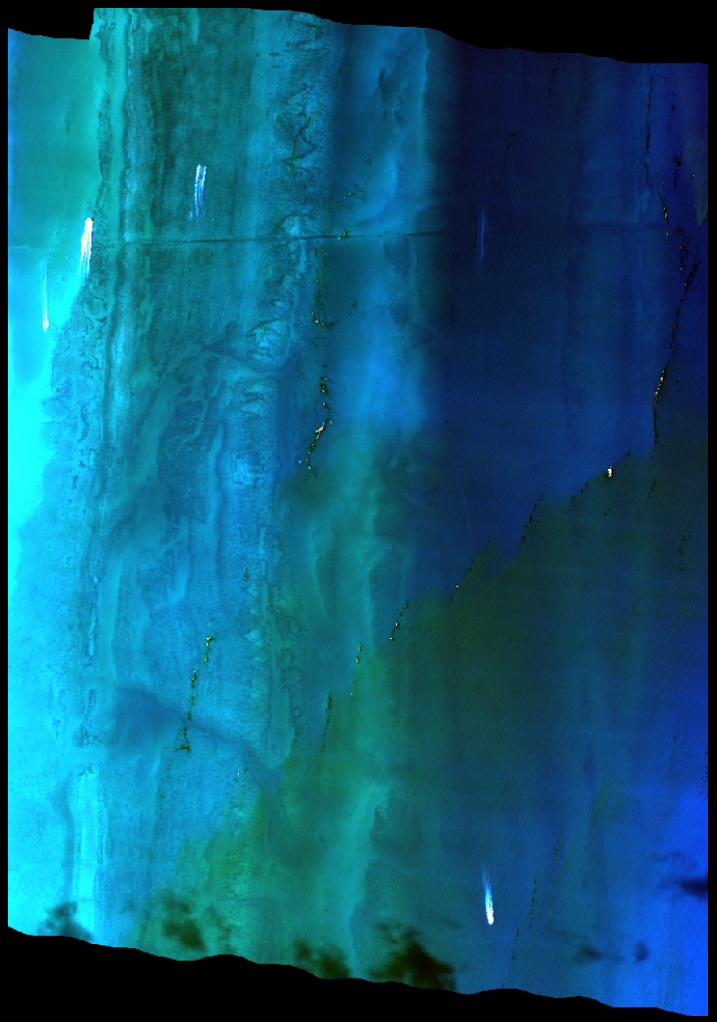
Case 2: Classification with CASI Seafloor Reflectance



CASI Surface Reflectance

CASI seafloor reflectance

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Case 2: Classification with CASI Seafloor Reflectance

CASI seafloor reflectance

MLC CASI Seafloor Reflectance

Shallow sand
Hardbottom 1
Mid sand
Hardbottom 2
Channel sand
Hardbotto
m 3
Deep
Reef
Sand

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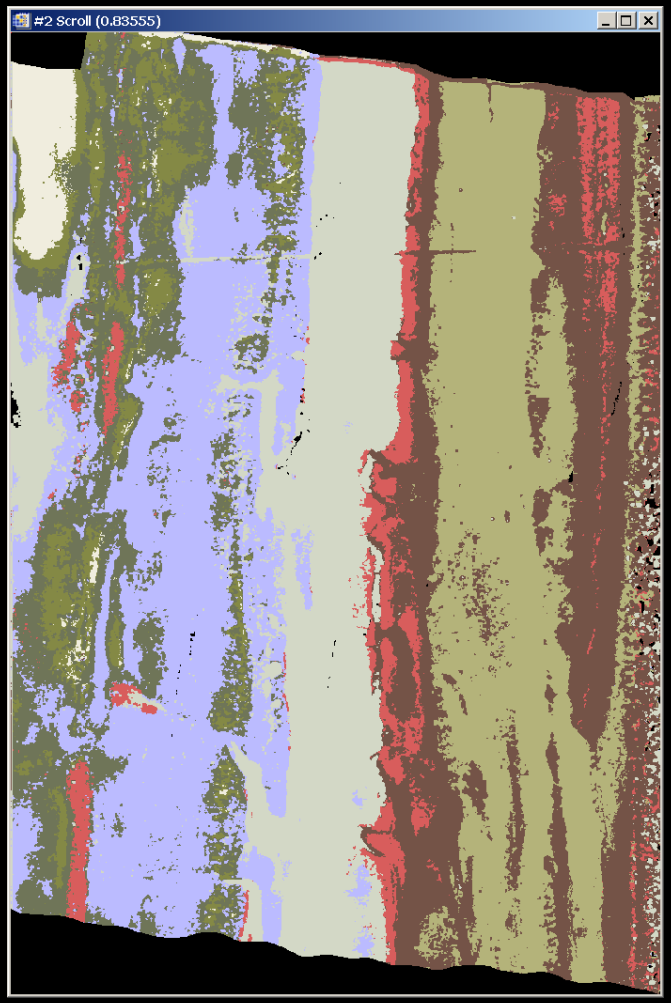
NOPP- Combining Classifiers using Dempster-Shafer

- The most useful benefit from Dempster-Shafer evidential theory is solving the conflicting problem between multiple data, based on a statistical approach.

MLC CASI Seafloor Reflectance



MLC SHOALS GLCM Texture

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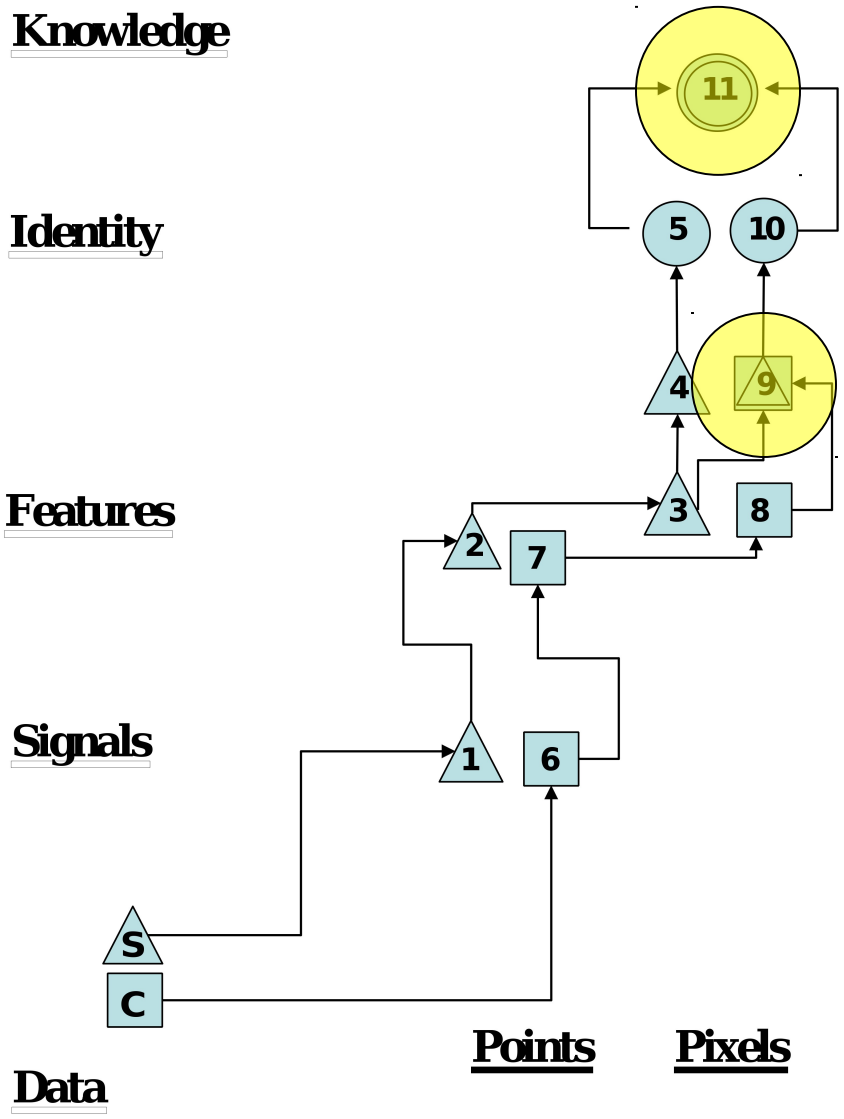
Case 3: Combining Classifiers using



1. Generate SHOALS calibrated waveforms at discrete points (P)
2. Estimate D, ρ_{532}, and K_{532}
3. Generate raster images for SHOALS
4. Quantize ρ_{532} image, use GLCM approach to extract texture metrics
5. Classify seafloor at pixel level using MLC on texture metrics
6. Generate Casi calibrated waveforms at discrete points (L_λ)
7. Pre-process Casi data to remove perturbing effects of atmosphere and sea surface (ρ_λ)
8. Generate ρ^s_λ image at geometric resolution of SHOALS images
9. Invert the RTE for Casi data using D, ρ_{532}, and K_{532} as constraints
10. Classify seafloor at pixel resolution using MLC or SAM
11. Use Dempster/Shafer Algorithm to create final classification

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Dempster's Rule of Combination

To apply Dempster-Shafer evidential theory, hypothesis and proposition should be decided first.

Hypothesis is a fundamental statement about nature (that is, an object is sand).

Proposition may be either a hypothesis or a combination of hypotheses and

		shal_sand	mid_sand	chan_sand	deep_sand	hb1	hb2	hb3	rf
		(sh_sVhb1)	(md_sVhb3)	(ch_sVhb1Vmd_s)	(dp_sVrf)	(hb1Vhb2Vsh_s)	(hb2Vhb1)	(hb3Vrf)	(dp_sVmd_sVrf)
shal_sand	(sh_sVhb1)	(sh_sVhb1)	k	hb1	k	(sh_sVhb1)	hb1	k	k
mid_sand	(md_sVhb3)	k	(md_sVhb3)	md_s	k	k	k	hb3	md_s
chan_sand	(ch_sVhb1Vmd_s)	hb1	md_s	(ch_sVhb1Vmd_s)	k	hb1	hb1	k	md_s
deep_sand	(dp_sVrf)	k	k	k	(dp_sVrf)	k	k	rf	(dp_sVrf)
hb1	(hb1Vhb2Vsh_s)	(sh_sVhb1)	k	hb1	k	(hb1Vhb2Vsh_s)	(hb2Vhb1)	k	k
hb2	(hb2Vhb1)	hb1	k	hb1	k	(hb2Vhb1)	(hb2Vhb1)	k	rf
hb3	(hb3Vrf)	k	hb3	k	rf	k	k	(hb3Vrf)	rf
rf	(dp_sVmd_sVrf)	k	md_s	md_s	(dp_sVrf)	k	rf	rf	(dp_sVmd_sVrf)

Dempster's Rule of Combination

- For the actual calculation of Dempster's rule of combination, we need to have the *priori* probabilities for the each proposition.
- The propositions can be acquired from the probabilities of each class in MLC.
- We made Dempster's rule of combination table with propositions for each class and actual probabilities from MLC

	casi	shal_sand	mid_sand	chan_sand	deep_sand	hb1	hb2	hb3	rf
shoals	Priori Probability	0.171609	0.0866691	0.0997276	0.0303565	0.222053	0	0.179819	0.209766
shal_sand	0.148709	0.0255198	0.0128885	0.0148304	0.00451428	0.0330214	0	0.026741	0.031194
mid_sand	0.133887	0.0229762	0.0116039	0.0133523	0.00406435	0.0297301	0	0.024076	0.028085
chan_sand	0.148099	0.025415	0.0128356	0.0147695	0.00449575	0.0328858	0	0.026631	0.031066
deep_sand	0	0	0	0	0	0	0	0	0
hb1	0.136268	0.0233847	0.0118102	0.0135896	0.0041366	0.0302587	0	0.024504	0.028584
hb2	0.153554	0.0263512	0.0133084	0.0153136	0.00466136	0.0340972	0	0.027612	0.03221
hb3	0.133083	0.0228382	0.0115342	0.0132721	0.00403994	0.0295516	0	0.023931	0.027916
rf	0.1464	0.0251235	0.0126884	0.0146001	0.00444418	0.0325086	0	0.026326	0.03071

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Concept of Evidential Theory

- The probability masses for each class are essential to calculate support function which is minimum probability for the class
- The support function for a proposition is the sum of the probability masses for a proposition

$$\text{Support (hb1)} = [m(hb1) + m(hb1 \veebar hb2) + (sh\_s \veebar hb1) + m(hb1 \veebar hb2 \veebar sh\_s)] / (1-C) = 0.483317277$$

$$= 0.40115$$

- Plausibility function is maximum probability for the class, which is the negation of doubt function which is the sum of all other probabilities excluding the class

$$\text{Doubt (hb1)} = 0.502516,$$
$$\text{Plausibility (hb1)} = 1 - \text{Doubt(hb1)} = 0.497484416,$$

- Evidential interval is the offset between plausibility function and support function

$$\text{Evidential interval} = \text{Plausibility(hb1)} - \text{Support(hb1)} = 0.014167$$

- The evidence for this conclusion is quite conclusive as indicated by a small uncertainty and a narrow evidential interval for hard bottom 1.

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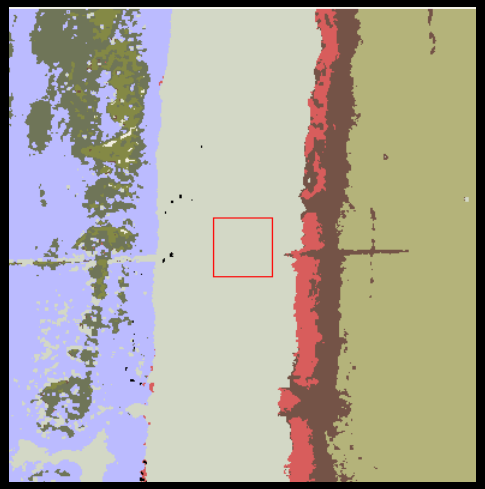
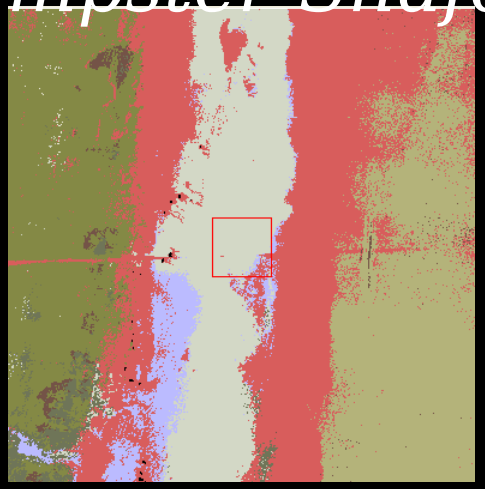
Case 3: Combining Classifiers using Dempster-Shafer

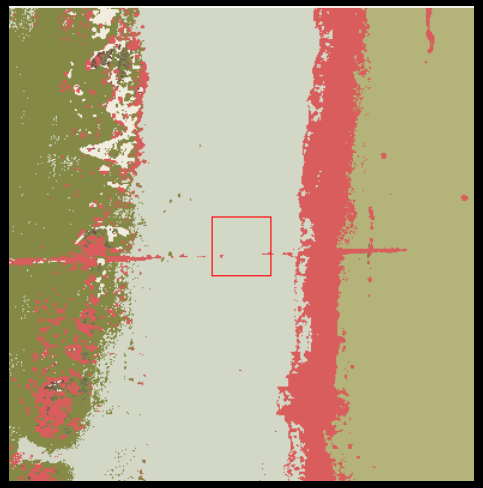


MLC SHOALS GLCM Texture

Dempster-Shafer's Evidential Theory



MLC CASI Seafloor Reflectance



Dempster-Shafer classification

- **Shallow sand**
- **Mid sand**
- **Channel sand**
- **Deep sand**
- **Hardbottom 1**
- **Hardbottom 2**
- **Hardbottom 3**
- **Reef**

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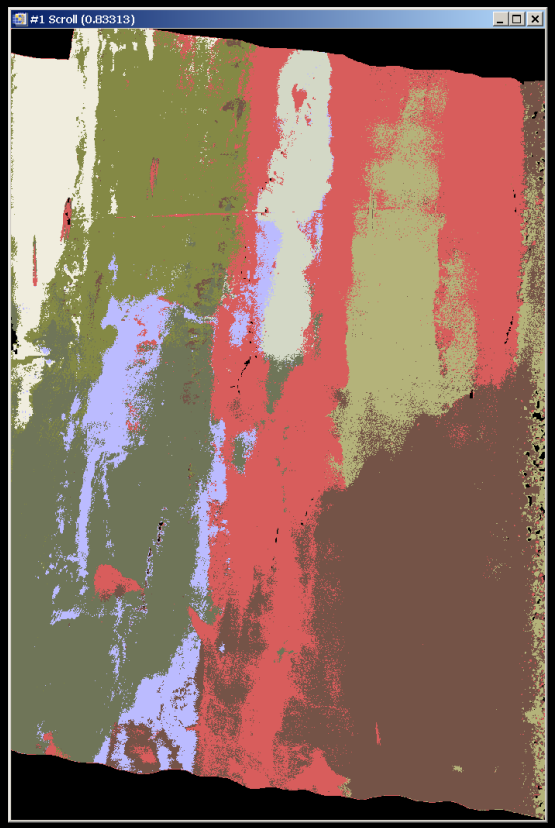
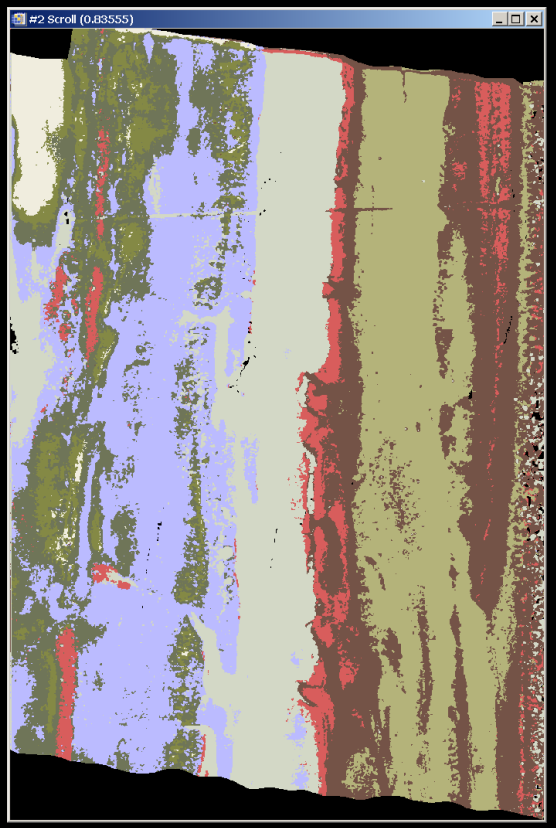
Case 3: Combining Classifiers using Dempster-Shafer

MLC CASI Seafloor Reflectance | MLC SHOALS GLCM Texture | Dempster-Shafer classificati





Overall accuracy : 61%

Overall accuracy : 69%

Overall accuracy : 89%

Accuracy Assessment using ground truth provided by NCRI of Nova S.E. Univ.

Shallow sand **Mid sand** **Channel sand** **Deep sand**
Hardbottom 1 **Hardbottom 2** **Hardbottom 3** **Reef**

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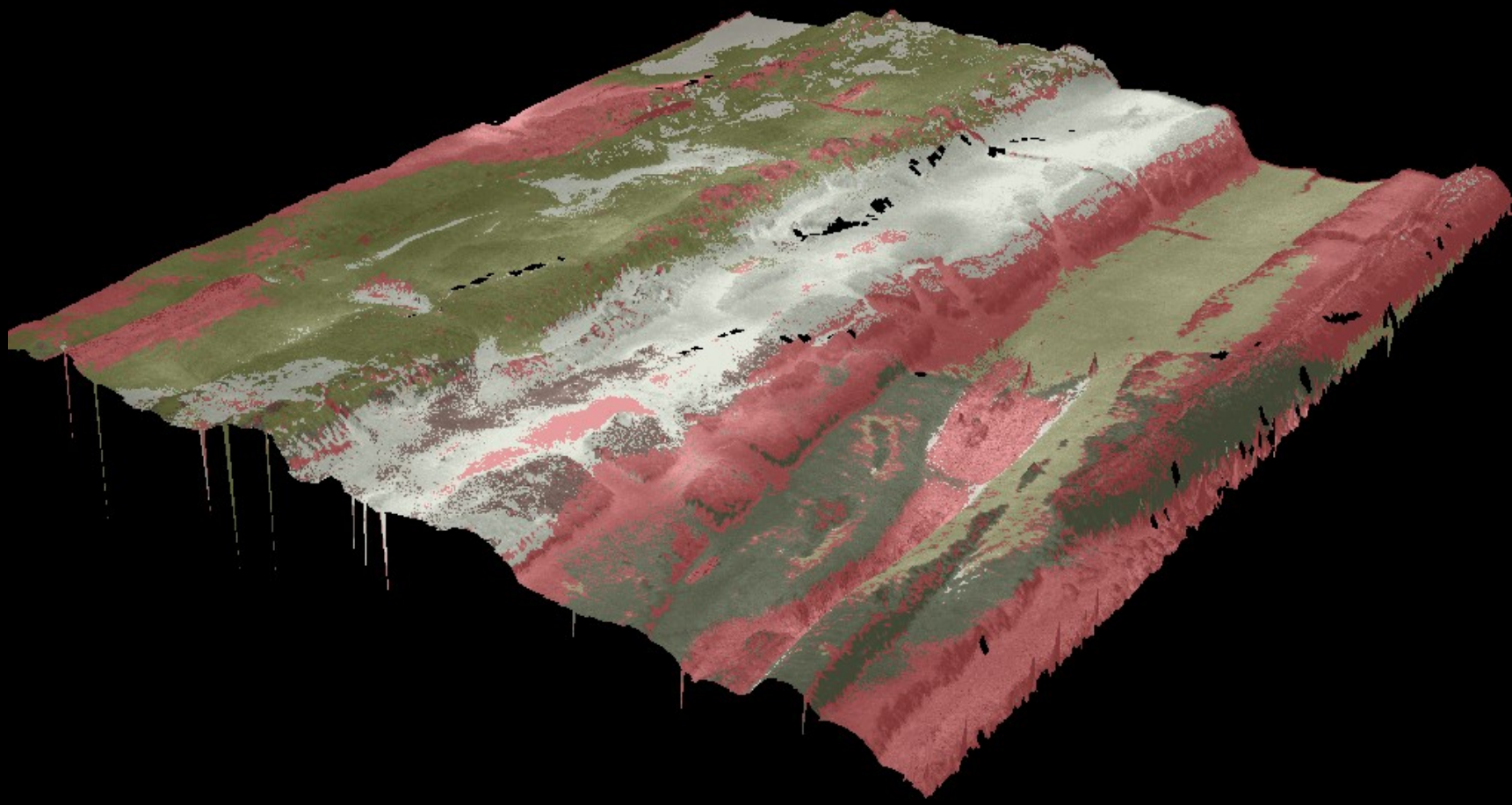

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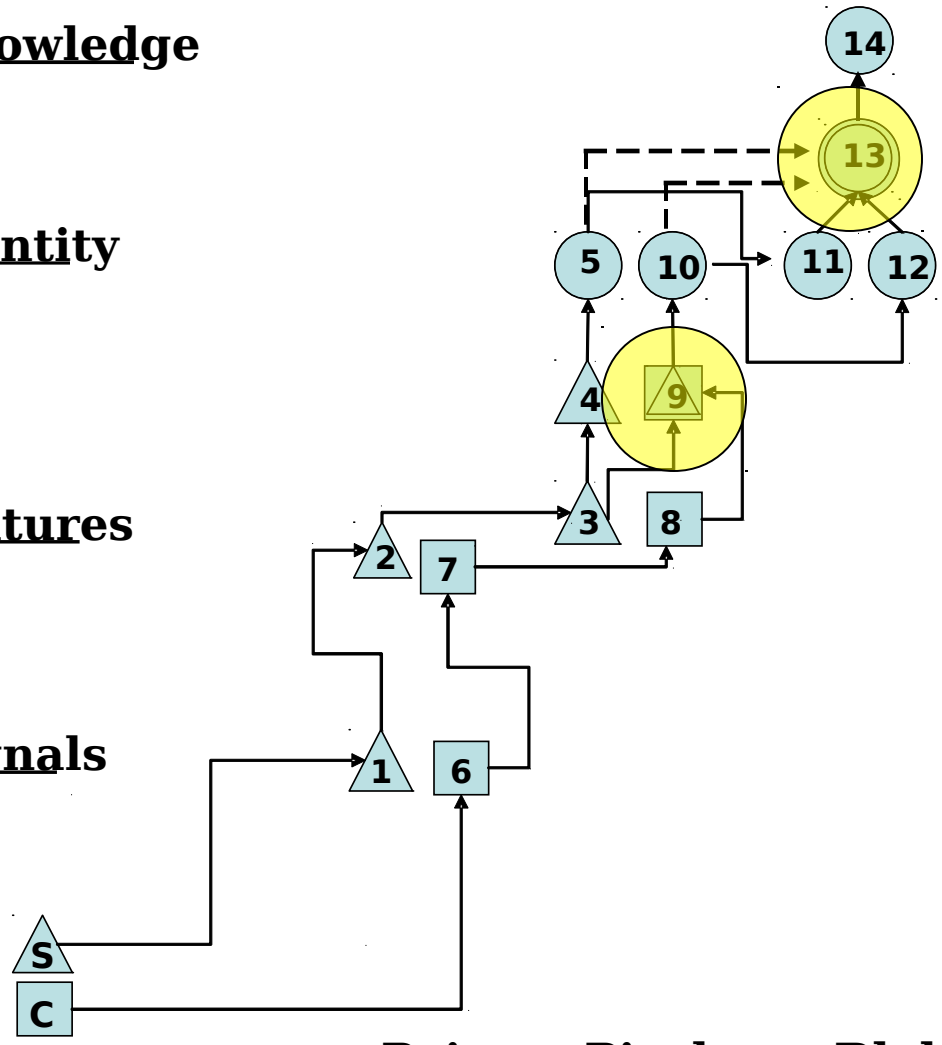
Case 4: Fusion Classification using Dempster-Shafer in Blobs



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8. Generate P^s_λ image at geometric resolution SHOALS images
9. Invert the RTE for Casi data using $D_{f,532}$ and K_{532} as constraints
10. Classify seafloor at pixel resolution using or SAM
11. Use Connected Neighbor algorithm to cre SHOALS Classification BLOBS
12. Use Connected Neighbor Algorithm to cre Casi Classification BLOBS
13. Use Set Intersections to join BLOBS, and pass probabilities from each MLC
14. Use Dempster-Shafer evidential theory in each blob to create final classification image

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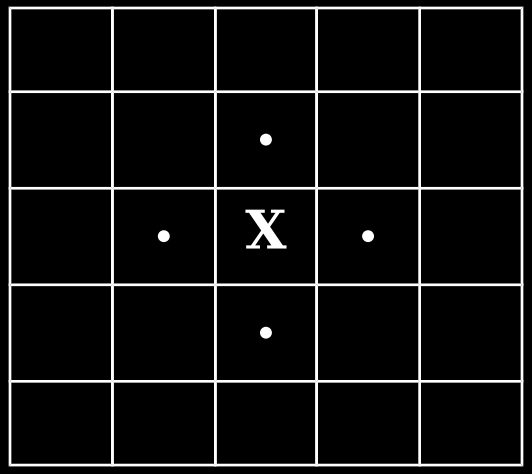
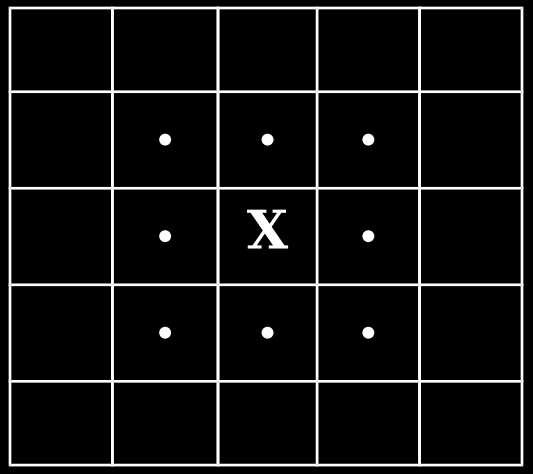
Connected Components Operators

"Blob" is defined as a region or connected component in the computer and robot vision community



4 connected components operator



8 connected components operator

0	1	1	0	1	0	0
0	1	1	0	1	0	1
1	1	0	0	1	1	1
0	0	0	0	0	0	1
0	1	1	1	0	0	0
0	1	1	1	1	0	0
0	1	1	1	0	1	0

0	1	1	0	2	0	0
0	1	1	0	2	0	2
1	1	0	0	2	2	2
0	0	0	0	0	0	2
0	3	3	3	0	0	0
0	3	3	3	3	0	0
0	3	3	3	0	3	0

Blobs by 8

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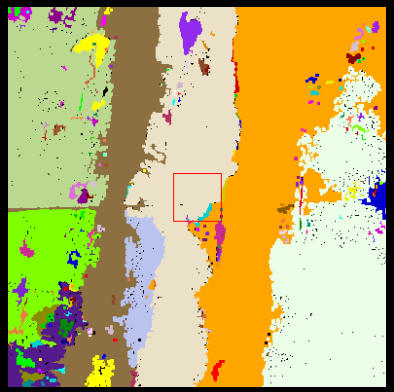
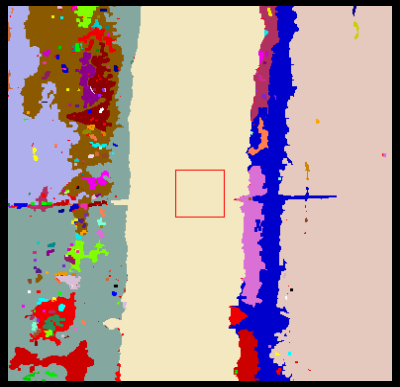
Blob Processing

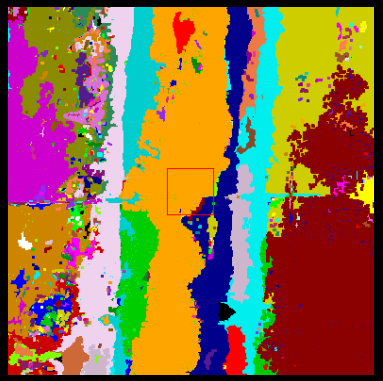


CASI Blobs

Set Theoretic Blob Intersection ∩



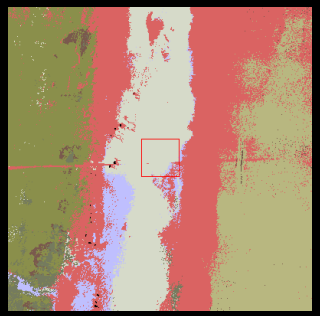
SHOALS Blobs



Intersection of Blobs

Pass the location of each blob

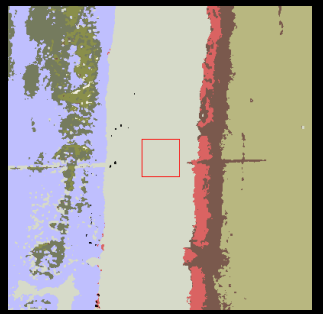
Pass the location of each blob



CASI MLC

Pass CASI mean MLC probability to each blob

Pass SHOALS mean MLC probability to each blob



SHOALS MLC

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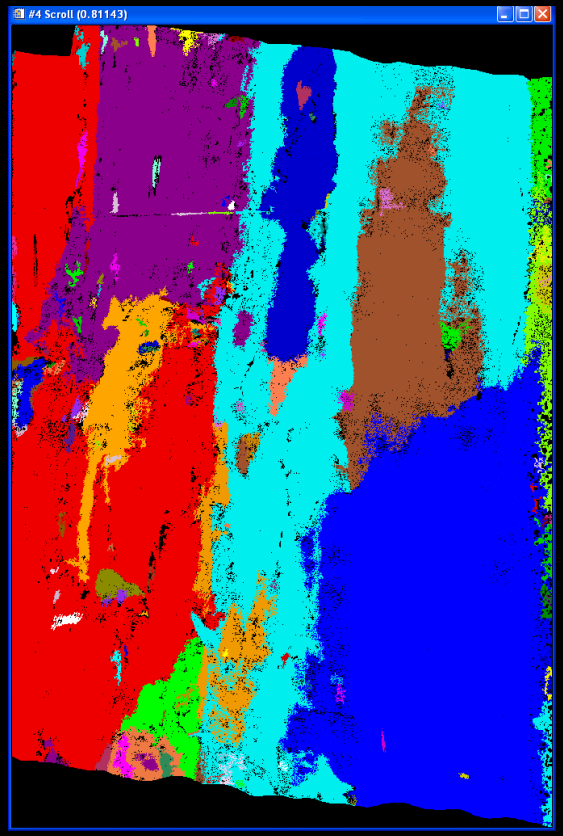
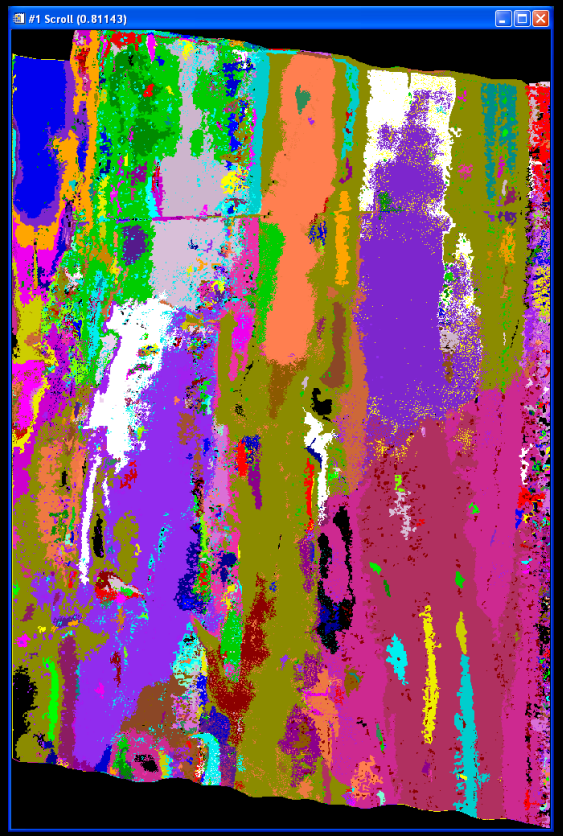
Case 4: Fusion Classification using Dempster-Shafer in Blobs





CASI Blob Image (183 blobs) SHOALS Blob Image (362 blobs) Intersected Blob Image (1199

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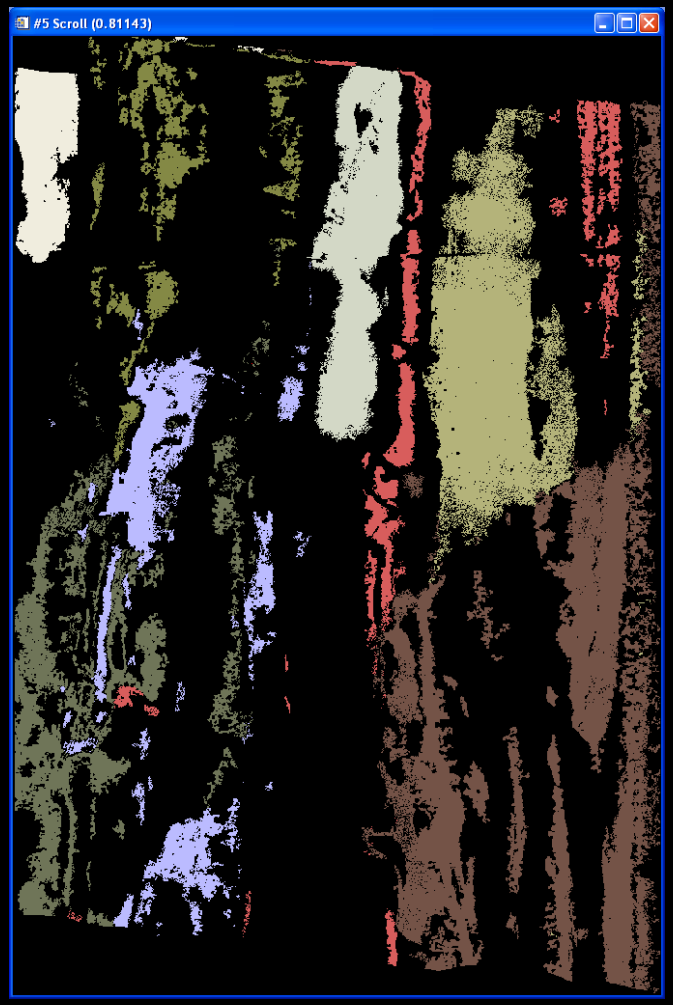
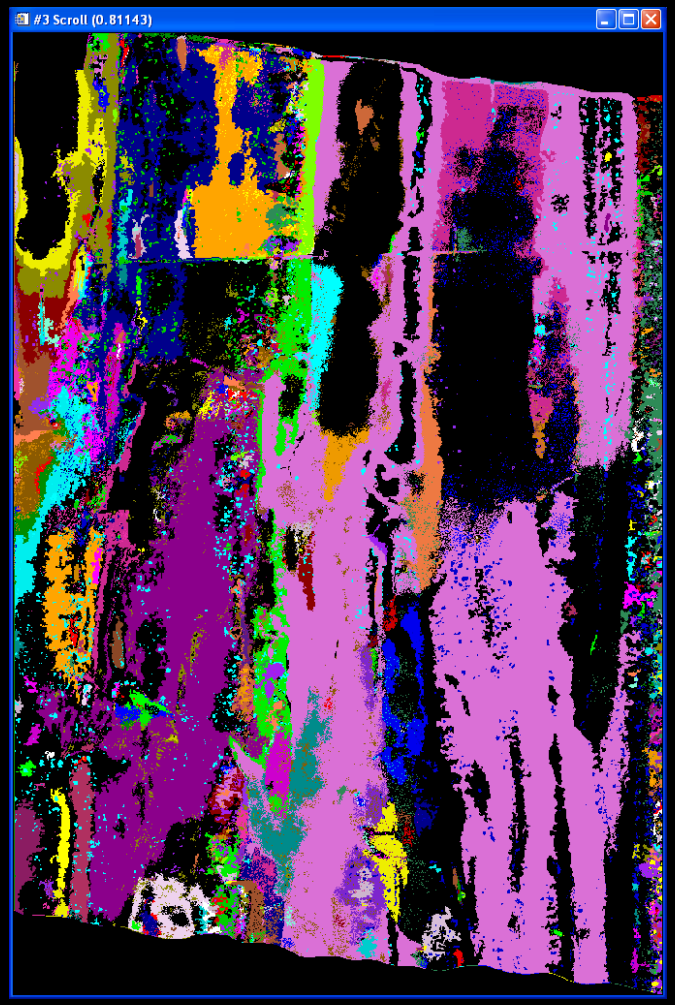
Case 4: Fusion Classification using Dempster-Shafer in Blobs

- To save processing time, Dempster-Shafer theory applied to only conflicting intersection blob area



Matching Intersection Blob Area



Conflicting Intersection Blob Area

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Case 4: Fusion Classification using Dempster-Shafer in Blobs

Data fusion classification image by Dempster-Shafer evidential theory in blobs

Shallow sand
Mid sand
Channel sand
Deep sand
Hardbottom 1
Hardbottom 2
Hardbottom 3
Reef

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Fusion classification images

Fusion classification image by D-S theory in pixels

Fusion classification image by D-S theory

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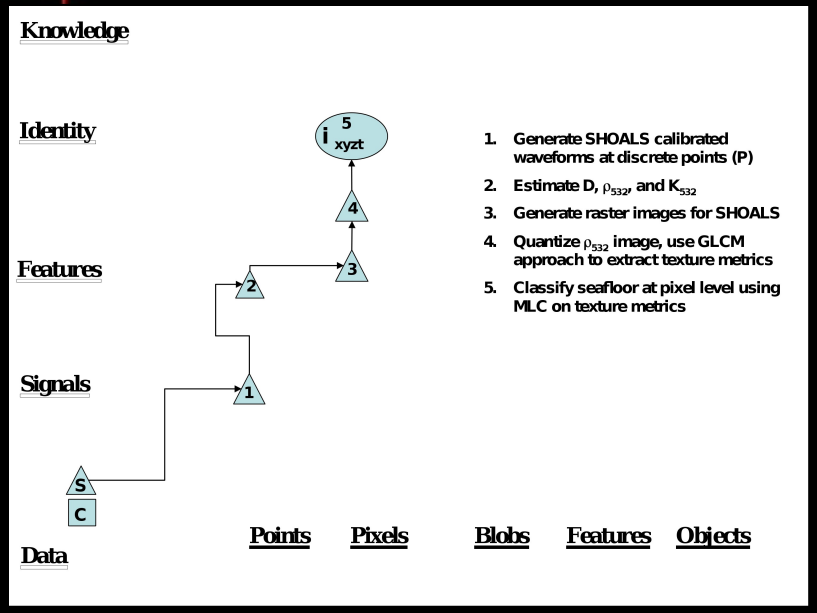

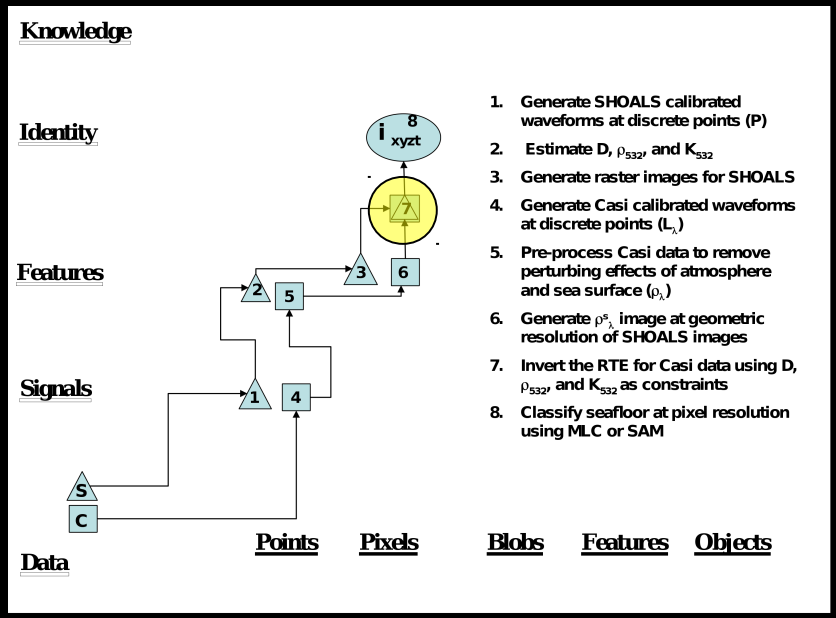

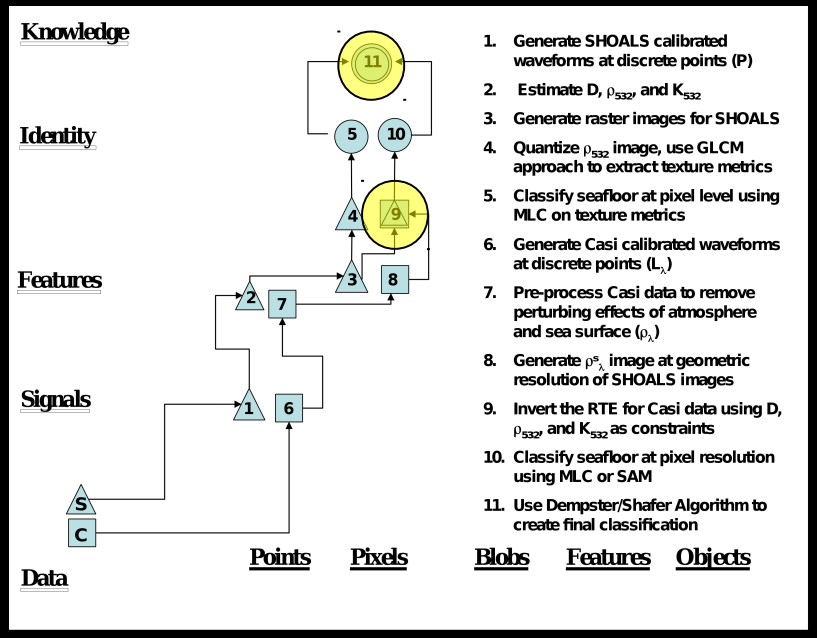

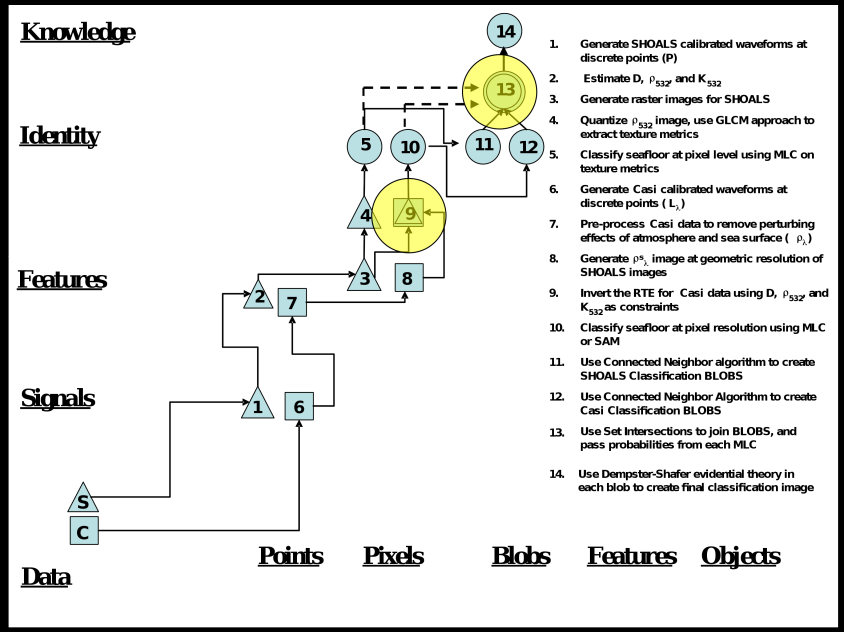
Knowledge
Identity
Features
Signals
Data
14
13
5
10
11
12
4
9
3
8
2
7
1
6
S
C
Points
Pixels
Blobs
Features
Objects
1. Generate SHOALS calibrated waveforms at discrete points (P)
2. Estimate D, ρ532, and K532
3. Generate raster images for SHOALS
4. Quantize ρ532 image, use GLCM approach to extract texture metrics
5. Classify seafloor at pixel level using MLC on texture metrics
6. Generate Casi calibrated waveforms at discrete points (Lλ)
7. Pre-process Casi data to remove perturbing effects of atmosphere and sea surface (ρλ)
8. Generate ρsλ image at geometric resolution of SHOALS images
9. Invert the RTE for Casi data using D, ρ532, and K532 as constraints
10. Classify seafloor at pixel resolution using MLC or SAM
11. Use Connected Neighbor algorithm to create SHOALS Classification BLOBS
12. Use Connected Neighbor Algorithm to create Casi Classification BLOBS
13. Use Set Intersections to join BLOBS, and pass probabilities from each MLC
14. Use Dempster-Shafer evidential theory in each blob to create final classification image

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Works to do in Year 2

- Refine Algorithm
  - Define blobs and pass probabilities from MLC pixels to blobs

- Find the options to get *a priori* probability.
  - ENVI Maximum likelihood classifier does not provide true probability

- Automate Dempster-Shafer computation
  - Automate decision of propositions
    - build proposition library for classes
  - Automate creation of Dempster's table

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Works to do in Year 2

- Research and test data fusion algorithms
  - Apply Automated Decision tree classifier
  - Research for Moving to features in spatial domain

- Refine IDL code
  - Memory management
  - Convenient user interface

- Accuracy assessment for final classifications from blobs

- Publish papers and presentations in conferences from the results of NOPP year 1

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